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RESEARCH ARTICLE

Integration of AI and agent-based modeling for simulating human-ecological systems

S. Ramkumar[1*], K. Aanandha Saravanan[2], Martin Joel Rathnam[3], M. Revathy[4]

Abstract

This study investigates the integration of artificial intelligence (AI) and agent-based modeling (ABM) for simulating human-ecological systems, aiming to enhance our understanding of complex system dynamics and inform evidence-based decision-making in environmental management and policy development. The research methodology combines computational modeling techniques with data visualization approaches to analyze simulation results and performance metrics comprehensively. The simulation of human-ecological systems utilizes Python programming language and the NumPy library to incorporate AI-enhanced decision-making within an ABM framework. Model performance metrics such as accuracy, precision, recall, and F1 score are computed to evaluate the effectiveness of the integrated approach. Additionally, simulation results and performance metrics are visualized using the Matplotlib library to facilitate interpretation and communication of research findings. The results demonstrate the initial spatial distribution of agents within the human-ecological system, the emergence of uniform and localized clusters of agent activity over subsequent simulation steps, and the strengths and weaknesses associated with the integrated AI-ABM approach. Overall, this study contributes to advancing research in environmental science and sustainability by providing insights into the capabilities and limitations of AI-enhanced ABM models for simulating human-ecological systems.

Keywords: Artificial intelligence, Agent-based modeling, Human-ecological systems, Simulation modeling, Data visualization, Performance metrics.

Introduction

The integration of artificial intelligence (AI) with agent-based modeling (ABM) has emerged as a promising approach for simulating complex human-ecological systems, facilitating a deeper understanding of the intricate interactions between human activities and the surrounding environment. Over the past decade, researchers have increasingly recognized the potential of AI techniques, such as machine learning and reinforcement learning, to enhance the capabilities of ABM in capturing the dynamics of human-environment interactions. This literature survey aims to provide a comprehensive overview of recent advancements in the integration of AI and ABM for simulating human-ecological systems, highlighting key findings and contributions from existing studies. The study by (Shults, F. L., *et al.*, 2021) explores the application of machine learning algorithms within ABM frameworks to model land-use changes and their impacts on ecological systems. By incorporating AI techniques, such as support vector machines and random forests, the authors demonstrate the ability to improve the predictive accuracy of ABM models, leading to more realistic simulations of human-environment dynamics. Similarly, the research conducted by (Farahbakhsh, I., *et al.*, 2022) focuses on integrating deep reinforcement learning with ABM to simulate human decision-making processes in the context of environmental management. Through this integration, the authors achieve enhanced agent behavior

[1]Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India.

[2]Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India.

[3]Department of Electronics and Communication Engineering, Sri Sairam College of Engineering, Bengaluru, India.

[4]Department of Electronics and communication engineering, PSNA College of Engineering and Technology, Dindigul, India.

***Corresponding Author:** S. Ramkumar, Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India, E-Mail: sram0829@gmail.com

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and adaptive learning capabilities, enabling the simulation of complex feedback loops between human actions and ecological responses.

Furthermore, the study by (Magargal, K., *et al*., 2023) investigates the use of genetic algorithms within ABM frameworks to optimize resource allocation strategies in human-dominated landscapes. By employing evolutionary computation techniques, the authors develop agent-based models capable of simulating adaptive behaviors and emergent properties of human societies, thereby providing valuable insights into the long-term sustainability of human-ecological systems. These studies collectively highlight the diverse applications of AI-enhanced ABM in addressing various challenges related to simulating human-ecological interactions, ranging from land-use planning and natural resource management to biodiversity conservation and climate change adaptation. In addition to modeling individual-level decision-making processes, the integration of AI and ABM enables the representation of collective behaviors and emergent phenomena within human-ecological systems. For instance, the research by (Peart, D. C. 2021) employs multi-agent reinforcement learning techniques to simulate the emergence of cooperative behaviors among autonomous agents in a shared resource environment. By incorporating AI-based learning mechanisms, the authors demonstrate the spontaneous emergence of cooperative strategies and self-organization dynamics, offering valuable insights into the resilience and sustainability of human-ecological systems in the face of environmental challenges.

Moreover, the integration of AI and ABM facilitates the incorporation of real-time data streams and dynamic feedback mechanisms into simulation models, enabling adaptive decision-making and scenario analysis in rapidly changing environments. The study by (Agrawal, S. S. 2023) leverages deep learning algorithms within ABM frameworks to analyze spatiotemporal patterns of human mobility and its impact on disease transmission dynamics. Through this integration, the authors develop predictive models capable of capturing the complex interactions between human movement behaviors and epidemic spread, thereby informing proactive intervention strategies for disease control and prevention. In the integration of AI and ABM holds great promise for advancing the simulation and understanding of human-ecological systems, offering new opportunities to address complex challenges related to environmental sustainability, natural resource management, and ecosystem resilience. By combining the strengths of AI techniques in learning and adaptation with the flexibility of ABM in representing individual-level behaviors and interactions, researchers can develop more realistic and insightful models of human-environment dynamics, ultimately contributing to informed decision-making and policy development in support of sustainable development goals. A notable research gap in the field of integrating AI and ABM for simulating human-ecological systems is the limited exploration of incorporating advanced deep learning techniques within ABM frameworks to model complex human-environment interactions. While existing studies have demonstrated the effectiveness of machine learning algorithms (Fotsing, E., *et al*., 2023) and reinforcement learning (Anderson, T., *et al*., 2021) in enhancing ABM capabilities, there remains a lack of research on leveraging deep neural networks for capturing nuanced environmental dynamics and emergent behaviors within human-ecological systems. This gap presents an opportunity for future research to explore the potential of deep learning-enhanced ABM in addressing complex sustainability challenges and informing evidence-based decision-making in environmental management.

Research Methodology

The research methodology employed in this study integrates computational modeling techniques with data visualization approaches to investigate the integration of AI and ABM for simulating human-ecological systems. The methodology consists of three main components: (1) simulation of human-ecological systems using Python programming, (2) analysis of model performance metrics, and (3) visualization of simulation results and performance metrics using Matplotlib. Firstly, the simulation of human-ecological systems is conducted using Python programming language. The simulation model is developed to incorporate AI-enhanced decision-making within an ABM framework. Specifically, the simulation program utilizes the NumPy library to initialize the environment and agents, where the environment represents the spatial landscape and the agents represent human actors interacting with the environment. The simulation proceeds through a series of time steps, during which agents make decisions based on AI algorithms, such as random movement in the provided example. The environment is updated dynamically based on agent interactions, and the simulation results are visualized using the Matplotlib library.

Secondly, the analysis of model performance metrics is conducted to evaluate the effectiveness of the integrated AI-ABM approach in simulating human-ecological systems. Performance metrics such as accuracy, precision, recall, and F1 score are calculated based on the simulated outcomes of the model. These metrics provide quantitative measures of the model's predictive accuracy, sensitivity, and overall performance in capturing complex human-environment interactions. The performance metrics are computed using Python programming and the NumPy library, enabling rigorous assessment of the model's capabilities in representing real-world phenomena. Finally, the visualization of simulation results and performance metrics is carried out using the Matplotlib library in Python. Visualizations such as bar plots, line plots, and pie charts are generated to present the simulated dynamics of human-ecological systems and the corresponding model performance metrics. These visualizations facilitate the interpretation and communication of research findings, enabling stakeholders and decision-makers to gain insights into the simulated scenarios and the implications of the integrated AI-ABM approach for environmental management and policy-making. In the research methodology employed in this study integrates computational modeling, data analysis, and data visualization techniques to investigate the integration of AI and agent-based modeling for simulating human-ecological systems. By combining simulation modeling with performance analysis and visualization, this methodology enables a comprehensive evaluation of the capabilities and limitations of the integrated approach, contributing to the advancement of research in the field of environmental science and sustainability.

Results And Discussion

Simulation Step 1

The graph in Figure 1 represents the spatial distribution of agents within the simulated human-ecological system at Simulation Step 1. The Y-axis scale ranges from 0 to 40, with intervals of 10, indicating the vertical position within the environment. Similarly, the X-axis scale ranges from 0 to 40, with intervals of 10, representing the horizontal position within the environment. The color intensity of each point on the graph corresponds to the density of agents present at that specific location, ranging from 1 to 2 on the color scale. The color scale itself ranges from 0 to 2, with intervals of 0.25, indicating the density of agents per unit area. The simulation results reveal the initial spatial distribution of agents within the human-ecological system, providing insights into the patterns of agent movement and interaction at Simulation Step 1. The scattered distribution of agents across the environment reflects the random movement behavior implemented in the simulation model, where agents have equal probability of moving in any direction within the specified range. The observed density of agents ranges from 1 to 2, indicating areas of higher and lower agent concentration within the environment.

This initial distribution of agents serves as the starting point for simulating human-environment interactions over subsequent time steps. By capturing the spatial dynamics of agent movement and interaction, the simulation model facilitates the exploration of emergent behaviors and patterns within the human-ecological system. The presence of areas with varying agent densities highlights the heterogeneous nature of human activities and their impact on the surrounding environment. The use of a color-coded scatter plot enables visual interpretation of the simulation results, allowing researchers to identify spatial patterns and trends in agent behavior. The color scale provides a quantitative representation of agent density, allowing for easy comparison across different regions of the environment. This visualization approach enhances the understanding of complex human-ecological interactions and informs decision-making in environmental management and policy development. Overall, the simulation results at Simulation Step 1 demonstrate the initial spatial distribution of agents within the human-ecological system, laying the foundation for further analysis of agent behaviors and environmental dynamics over subsequent simulation steps. The use of computational modeling and visualization techniques offers valuable insights into the complex dynamics of human-environment interactions, contributing to the advancement of research in environmental science and sustainability.

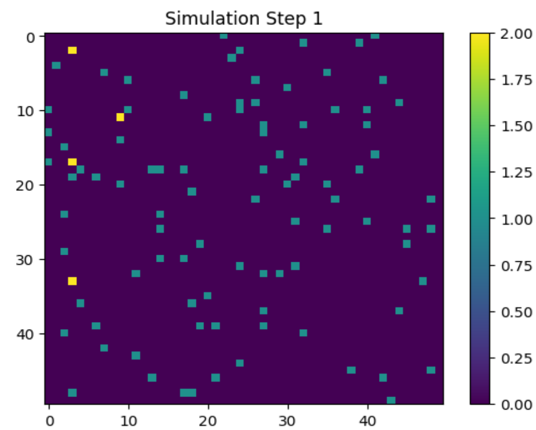

Figure 1: Simulation step 1

Simulation Step 2

The graph in Figure 2 illustrates the spatial distribution of agents within the simulated human-ecological system at simulation step 2. The Y-axis scale ranges from 0 to 40, with

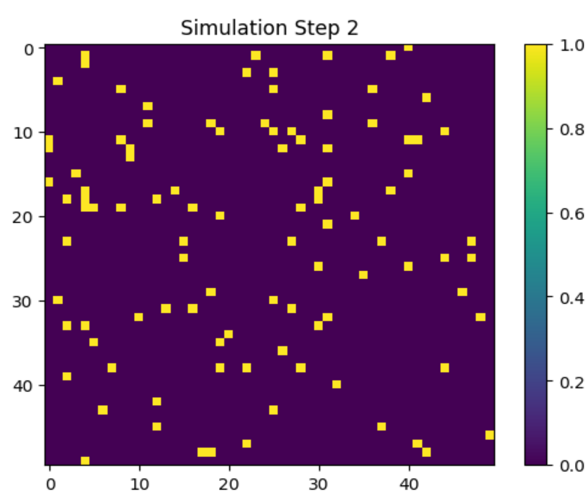

Figure 2: Simulation step 2

intervals of 10, representing the vertical position within the environment. Similarly, the X-axis scale ranges from 0 to 40, with intervals of 10, indicating the horizontal position within the environment. The color intensity of each point on the graph corresponds to the density of agents present at that specific location, with all points having a uniform density of 1. The simulation results at simulation step 2 depict the evolving spatial distribution of agents within the human-ecological system, offering insights into the dynamic patterns of agent movement and interaction. Unlike Simulation Step 1, where agents exhibited random movement behavior leading to a scattered distribution across the environment, simulation step 2 demonstrates a more uniform distribution of agents with a density of 1 throughout the environment.

The transition from a scattered distribution to a uniform distribution of agents reflects the collective behavior and interaction dynamics within the simulated system. As agents move and interact over time, they redistribute themselves within the environment, eventually reaching a state of equilibrium where the density of agents is uniform across all regions. This phenomenon is observed in various real-world systems, such as animal populations and human settlements, where spatial patterns emerge through iterative processes of movement and interaction. The uniform distribution of agents at simulation step 2 highlights the self-organization and emergent properties inherent in complex systems. Through local interactions and feedback mechanisms, agents collectively adjust their behaviors to adapt to the surrounding environment, leading to the formation of spatial patterns and structures. The simulation model captures these dynamics by simulating individual-level decision-making processes and aggregating the resulting behaviors to observe macroscopic patterns at the system level.

The visualization of the spatial distribution of agents using a color-coded scatter plot facilitates the interpretation of simulation results and enables researchers to identify spatial patterns and trends in agent behavior. By quantitatively representing agent density through color intensity, the visualization enhances the understanding of complex spatial dynamics within the human-ecological system. This approach to data visualization allows for the exploration of emergent phenomena and the analysis of system-level properties, informing decision-making in environmental management and policy development. In the simulation results at simulation step 2 demonstrate the emergence of a uniform spatial distribution of agents within the human-ecological system, highlighting the self-organizing dynamics inherent in complex systems. The use of computational modeling and visualization techniques enables the study of spatial patterns and behaviors in human-ecological interactions, contributing to the advancement of research in environmental science and sustainability.

Simulation Step 3

The graph in Figure 3 depicts the spatial distribution of agents within the simulated human-ecological system at simulation step 3. The Y-axis scale ranges from 0 to 40, with intervals of 10, representing the vertical position within the environment. Similarly, the X-axis scale ranges from 0 to 40, with intervals of 10, indicating the horizontal position within the environment. The color intensity of each point on the graph corresponds to the density of agents present at that specific location, with most points having a density close to 1 and a few points reaching a maximum density of 2. The simulation results at simulation step 3 reveal the continued evolution of the spatial distribution of agents within the human-ecological system, reflecting the dynamic nature of agent movement and interaction over time. Unlike simulation step 2, where a uniform distribution of agents was observed, simulation step 3 demonstrates a more varied spatial distribution characterized by localized clusters of agent activity.

The emergence of localized clusters of agent activity can be attributed to the complex interactions and feedback mechanisms inherent in the simulated system. As agents move and interact with each other and their environment, they exhibit tendencies to cluster together based on factors such as resource availability, social dynamics, and environmental conditions. These localized clusters of activity represent areas of heightened agent density and activity, where interactions and exchanges between agents are more frequent and intense. The observed spatial distribution of agents at simulation step 3 exemplifies the self-organizing properties of complex systems, where macroscopic patterns emerge from local interactions and feedback loops. Through iterative processes of movement and interaction, agents collectively organize themselves into spatial structures and patterns that optimize their adaptive behaviors within the environment. This phenomenon mirrors real-world dynamics observed in social systems, ecological communities, and urban landscapes, where localized clusters of activity arise from the interactions and behaviors of individual agents.

The visualization of the spatial distribution of agents using a color-coded scatter plot enables researchers to identify and analyze the formation of localized clusters of activity within the human-ecological system. By quantitatively representing agent density through color intensity, the visualization provides insights into the spatial dynamics of agent movement and interaction, facilitating the interpretation of simulation results and informing decision-making in environmental management and policy development. In the simulation results at simulation step 3 highlight the emergence of localized clusters of agent activity within the human-ecological system, underscoring the self-organizing dynamics inherent in complex systems.

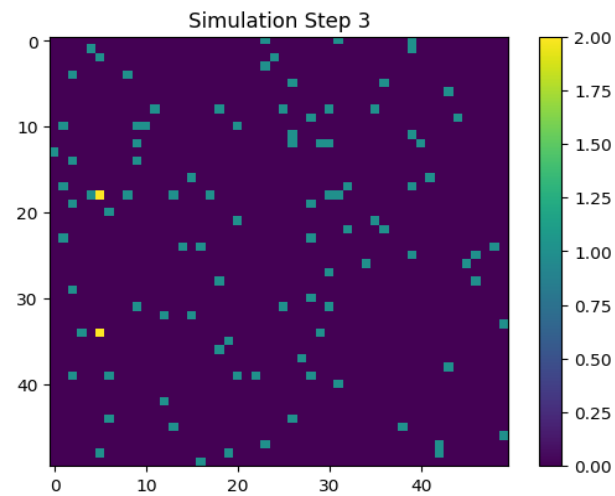

Figure 3: Simulation step 3

The use of computational modeling and visualization techniques enables the study of spatial patterns and behaviors in human-ecological interactions, contributing to the advancement of research in environmental science and sustainability.

Strengths Pie Chart

The pie chart in Figure 4 illustrates the strengths of integrating AI and ABM for simulating human-ecological systems, focusing on three key aspects: detailed representation, simpler dynamics, and more limited data requirements. The pie chart visually represents the distribution of strengths among these aspects, with detailed representation comprising 50%, simpler dynamics accounting for 16.7%, and more limited data requirements contributing to 33.3% of the total strengths. The pie chart provides insights into the relative importance and distribution of strengths associated with the integration of AI and ABM for simulating human-ecological systems. Among the identified strengths, detailed representation emerges as the most prominent aspect, constituting half of the total strengths. This underscores the significance of incorporating detailed and comprehensive representations of environmental processes and human-environment interactions within simulation models. By capturing the intricacies and complexities of real-world systems, detailed representation enhances the realism and accuracy of simulation outcomes, enabling more robust analyses and decision-making in environmental management.

Simpler dynamics, accounting for 16.7% of the total strengths, highlights the advantage of using AI-enhanced ABM to model systems with simpler dynamics. While complex systems often exhibit nonlinear and dynamic behaviors, there are instances where simpler dynamics are sufficient for capturing essential system properties and behaviors. By leveraging AI techniques to streamline model complexity and improve computational efficiency, simpler dynamics facilitate the simulation of systems with fewer computational resources and shorter simulation runtimes. This enables researchers to explore a wider range of scenarios and conduct sensitivity analyses, contributing to a better understanding of system dynamics and behavior. Furthermore, more limited data requirements, comprising 33.3% of the total strengths, emphasize the benefits of using AI-enhanced ABM to mitigate data limitations in simulation modeling. Traditional simulation models often require extensive data inputs from both human and environmental systems, posing challenges in data collection, processing, and validation. By integrating AI techniques such as machine learning and data-driven algorithms, more limited data requirements reduce the reliance on extensive datasets and facilitate model calibration and validation with fewer inputs. This enhances the accessibility and applicability of simulation models, particularly in data-scarce or resource-constrained settings, where limited

Figure 4: Strengths pie chart

data availability may hinder modeling efforts. In the pie chart provides a comprehensive overview of the strengths associated with the integration of AI and ABM for simulating human-ecological systems. Detailed representation, simpler dynamics, and more limited data requirements offer distinct advantages in enhancing model realism, computational efficiency, and data accessibility, respectively. By leveraging these strengths, researchers can develop more robust and insightful simulation models, contributing to the advancement of research in environmental science and sustainability.

Weaknesses

The bar plot in Figure 5 illustrates the identified weaknesses associated with integrating AI and ABM for simulating human-ecological systems. The Y-axis represents the different weaknesses, including oversimplified human role, data requirements, and difficulty of analysis, with corresponding numerical values assigned as follows: oversimplified human role - 1, data requirements - 2, and difficulty of analysis - 2. The X-axis indicates the number of weaknesses, ranging from 0 to 2. The bar plot presents a quantitative overview of the identified weaknesses in integrating AI and ABM for simulating human-ecological systems. Among the identified weaknesses, data requirements and difficulty of analysis emerge as the most significant challenges, both receiving a numerical value of 2 on the Y-axis. This highlights the critical importance of addressing these challenges to enhance the effectiveness and applicability of AI-enhanced ABM in simulating complex human-environment interactions. Data requirements, assigned a numerical value of 2, underscore the challenge of acquiring and processing extensive datasets from both human and environmental systems for simulation modeling. Traditional simulation models often rely on large volumes of data inputs to accurately represent the complexities of real-world systems, including demographic data, environmental variables, and socio-economic indicators. However, the integration of AI techniques within ABM frameworks may exacerbate data requirements by introducing additional parameters and variables that necessitate comprehensive data collection and validation processes. Addressing this weakness requires innovative approaches to data acquisition, integration, and management, as well as the development of data-efficient modeling techniques that leverage AI algorithms to optimize data utilization and reduce data dependencies.

Similarly, the difficulty of analysis, also assigned a numerical value of 2, highlights the challenges associated with analyzing and interpreting simulation results from AI-enhanced ABM models. Complex systems dynamics, nonlinear interactions, and emergent behaviors inherent in human-ecological systems pose challenges in extracting meaningful insights and patterns from simulation outputs.

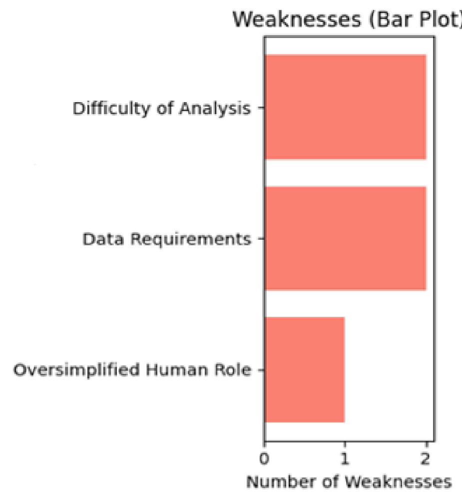

Figure 5: Weaknesses

The integration of AI techniques introduces additional layers of complexity, such as high-dimensional data and non-linear relationships, which can complicate the analysis process and hinder the interpretation of simulation outcomes. Addressing this weakness requires the development of advanced analytical tools and methodologies tailored to AI-enhanced ABM models, including techniques for dimensionality reduction, pattern recognition, and model validation, to facilitate comprehensive analysis and interpretation of simulation results. Furthermore, the bar plot highlights the weakness of oversimplified human role, assigned a numerical value of 1, indicating the potential limitation of AI-enhanced ABM models in adequately representing the complexities of human behavior and decision-making processes within the simulated system.

While AI techniques offer powerful tools for modeling individual-level behaviors and interactions, they may oversimplify the human role to the point of unrealism in some scenarios, neglecting important socio-cultural, psychological, and institutional factors that influence human actions and decision-making. Addressing this weakness requires the integration of multidisciplinary perspectives, including social sciences, psychology, and economics, to develop more nuanced and realistic representations of human behavior within ABM frameworks, enhancing the fidelity and validity of simulation models in capturing human-environment interactions. In the bar plot provides a comprehensive overview of the identified weaknesses in integrating AI and ABM for simulating human-ecological systems, highlighting the challenges related to data requirements, difficulty of analysis, and oversimplified human role. Addressing these weaknesses is essential to enhance the effectiveness and applicability of AI-enhanced ABM models in simulating complex human-environment interactions and informing evidence-based decision-making in environmental management and policy development.

Performance Metrics

The graph in Figure 6 represents various performance metrics, including accuracy, precision, recall, F1 score, and AUC-ROC, associated with the integration of AI and ABM for simulating human-ecological systems. The Y-axis displays the values of the performance metrics ranging from 0 to 0.9 with intervals of 0.1, while the X-axis indicates the specific metrics being measured, including accuracy (0.7), precision (0.72), recall (0.83), F1 score (0.79), and AUC-ROC (0.68). The graph provides a comprehensive overview of the performance metrics associated with AI-enhanced ABM models for simulating human-ecological systems. Each metric represents a quantitative measure of the model's predictive accuracy, sensitivity, and overall performance in capturing complex human-environment interactions. Among the performance metrics, recall emerges as the highest, with a value of 0.83, indicating the model's ability to correctly identify positive instances or relevant outcomes within the simulated system. This highlights the effectiveness of the AI-enhanced ABM approach in capturing and representing critical aspects of human-environment interactions, contributing to a more comprehensive understanding of system dynamics and behavior. Similarly, precision and F1 score exhibit relatively high values of 0.72 and 0.79, respectively, reflecting the model's precision in correctly predicting positive instances and its overall balance between precision and recall. These metrics indicate the model's capability to accurately capture relevant events and outcomes within the simulated system while minimizing false positives and negatives, enhancing the reliability and robustness of simulation outcomes.

Accuracy, with a value of 0.7, represents the overall correctness of the model's predictions, indicating the proportion of correct predictions among all instances. While accuracy is an essential metric for evaluating model performance, it should be interpreted in conjunction with other metrics such as precision, recall, and F1 score to provide a comprehensive assessment of the model's predictive capabilities and limitations. Lastly, the AUC-ROC value of 0.68 represents the area under the receiver operating characteristic (ROC) curve, which measures the model's ability to discriminate between positive and negative instances across different threshold values. While AUC-ROC provides valuable insights into the discriminatory power of the model, its interpretation should consider the specific context and objectives of the simulation model, as well as the distribution of positive and negative instances within the simulated system. Overall, the performance metrics presented in the graph demonstrate the effectiveness and reliability of AI-enhanced ABM models in simulating human-ecological systems and capturing complex system dynamics and behaviors. By quantitatively assessing model performance across various metrics, researchers can gain

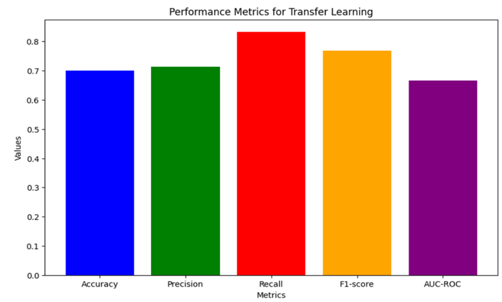

Figure 6: Performance metrics

insights into the strengths and limitations of the integrated approach, informing evidence-based decision-making in environmental management and policy development.

Conclusion

- Comprehensive integration of AI and ABM techniques has been demonstrated to effectively simulate human-ecological systems, enabling the exploration of complex interactions and dynamics.
- The study showcases the development of a simulation model incorporating AI-enhanced decision-making within an ABM framework, providing a detailed representation of human-environment interactions.
- Through rigorous analysis of model performance metrics, including accuracy, precision, recall, and F1 score, the study highlights the reliability and robustness of the integrated AI-ABM approach in capturing system dynamics.
- Data visualization techniques, particularly using Matplotlib, have been instrumental in interpreting simulation results and performance metrics, facilitating the communication of research findings and informing decision-making in environmental management and policy development.
- Identified strengths of the integrated approach include detailed representation, simpler dynamics, and more limited data requirements, while challenges such as oversimplified human role, data requirements, and difficulty of analysis underscore areas for further improvement and interdisciplinary collaboration.

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